## Deep learning for cellular image analysis - Erick Moen et.al

Summary:

The paper talks about the advancements in imaging and how it has influenced the research in medical image analysis. It talks about platforms like MATLAB which provide several traditional computer vision tools to address tasks like object tracking and image classification. The paper further highlights how such tools have helped researchers work on problems that seemed infeasible earlier. Deep learning further widened the range of problems computer vision can solve.

Although there is a lot of research and development happening in computer vision, it is not widely used in life-science research. One of the reasons is the black-box nature of deep learning models. Along with it, a high amount of trainable data and computation power is required to train these deep learning networks.

One of the key aspects of deep learning is data. Generating data, which is annotation error-free, is sufficient and captures all the possible variability of the dataset is costly, time-taking and tedious. Although there are many techniques like data augmentation, transfer learning which can be used when the training dataset size is small, they only help so much. A significant performance boost is achieved when the actual dataset size is increased.
Once we have enough good quality training data, we can train deep learning models to make predictions on test data accurately. There are many deep learning frameworks like TensorFlow/Keras, PyTorch, Caffe, CNTK, Theano, and MXnet which can be used to implement deep learning models. These frameworks have their differences, but also are similar in the ways they make use of GPU resources, initialize computational graphs, and much more.

Complex deep learning architectures, also known as high model capacity architectures are very prone to overfitting when training data is limited. Simple deep learning architectures, also known as low model capacity architectures tend to underfit. It is suggested to use a model with limited capacity along with regularization to develop robust models. Hyperparameter tuning is also important.
After model training, the next step is deployment. Deep learning frameworks like Tensorflow have deployment pipelines that can easily be used to deploy the trained models. Containerization is also quite useful for fast deployment. Cloud infrastructure also comes in handy when deploying deep learning models. Keren et al. leveraged cloud infrastructure to deploy deep learning models to quantify spatial proteomics data of the tumor microenvironment. The tool was named CDeep3M.

One of the important use cases where deep learning can be applied to biomedical applications is image classification. One such application is identifying whether a protein is expressed in the cytoplasm or the nucleus on the basis of fluorescence. In classification tasks, the use of transfer learning has fetched great outcomes recently. Due to the non-availability of enough annotated data for training, pre-trained models on huge datasets like imagenet can be used as a great starting point for training models on small medical image datasets.

Segmentation is another computer vision task, which can also be useful in many medical image analysis tasks. An application where we can use segmentation is for identifying a single cell in microscopic images.

Object tracking is another area where computer vision can be used with medical data. Object tracking is a combination of object detection and object linkage. Object linkage can be achieved using classical approaches like nearest neighbor search and linear programming. Jaqaman et al in their work addressed complex behavior of objects like splitting, disappearing using linear programming. This approach is used in software like TrackMate and CellProfiler.
Due to the 3D nature of object tracing, training data accumulation for deep learning is difficult. Nonetheless, deep learning models are still used for object detection which is quite an important step in object tracking.

Another application of computer vision in medical images is augmented microscopy. Augmented microscopy is the extraction of latent information from medical images. Although methods like phase-contrast microscopy and differential interference contrast microscopy could generate information, extraction of that information is computationally intensive. Scientists addressed this problem by translating it to a supervised learning problem

The application of deep learning in medical image analysis, although in its early stages, has had a remarkable effect on the field. A collaborative effort should be made to further strengthen this field.